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# 1989 AFIT Neural Network Research

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## Abstract

This paper will provide a brief summary of recent research at the Air Force Institute of Technology (AFIT) in the area of Neural Networks. Specifically, AFIT research into the areas of back-propagation relations to conventional algorithms, feature selection, neural networks for segmentation or general purpose pre-processing, angle of arrival detection, speech recognition, optical neural networks and brain implants will be presented.

## 1 Introduction

Over the last several years, AFIT has been investigating neural networks for military applications. During 1989, the research group consisted of masters, PhD students and faculty totaling approximately twenty people. This paper covers some of the work from this group.

## 2 Back Propagation as a Degenerate Kalman Filter

Several major accomplishments were made in the last six months. We were able to show that the most common learning algorithm, backpropagation, used for feedforward artificial neural networks is just a degenerate version of an extended Kalman filter. In essence the result shows that with certain degenerate assumptions the extended Kalman algorithm becomes the backpropagation algorithm. This result allows us to call upon AFIT's rich experience in Kalman Filtering to determine the applicability of these networks. On the other hand, if the degenerate assumptions were not made and the full extended Kalman filter was used to train the weights, how are the learning results affected? Figure 1 shows the results of training networks using both conventional backpropagation and the extended Kalman filter on a mesh problem with interconnected, disjoint regions. One sees that the Kalman filter learns with fewer iterations. If the comparison were made on the number of computations, the Kalman algorithm is far more intensive than the conventional backpropagation. When more realistic problems in target recognition are tested, the advantages of learning are not as dramatic. Figure 2 shows both algorithms learning from absolute range data and accuracies are similar for a given number of iterations. This result emphasizes the importance of using real data when developing new learning algorithms.

## 3 Conventional Statistical Techniques *versus* Neural Based Classifiers

A second major accomplishment was the comparison of the results of using artificial neural networks to classify tactical target data with conventional classification techniques. The major result here is that the networks can do about as well as the optimum statistical classification technique. The implication of this is that we will not base the use or non-use of a neural network classifier on desired accuracy but potentially on other factors such as cost, robustness or even speed. In Table 1 we see the comparison of a conventional non-parametric Bayesian based classifier and a neural network and the accuracies show no statistically meaningful differences. A fundamental mathematical tie between these approaches is now being investigated, analogous to the extended Kalman filter backpropagation tie.

## 4 Feature Selection

A third major accomplishment of the research group was the determination of a method of finding the importance of features for use by a neural network classifier. Specifically, in a tactical target problem we submitted a set of features and trained the network to tell the difference between the different targets and non-target blobs found by our automatic segmentor. Using our method, we could determine which of the features were important in the discrimination of the classes. The importance here is that we no longer have to know *a priori* what is the right set of features but we allow the network to determine it from every feature we as the system designer think might be relevant. We have also demonstrated fusing information from multiple sensors. In fact, we have demonstrated neural networks for fusing information from multiple sensors increasing probabilities of detection without significantly increasing the false alarm rates. These ideas of having an automatic system for architecting networks, selecting features and fusing information for a given problem will allow this technology to be used by non-neural network people to solve their problems.

## 5 Segmentation

We also developed techniques for using neural networks for image segmentation. To accomplish this, we used two techniques. First we tested the use of Hough transforms on discrimination of SAR images of objects. The biological connection here is the postulated existence of line detectors in the primary visual cortex (Hubel and Wiesel). We believe that a better model is that

of the Gabor transform and a technique to segment FLIR images using Gabor transforms was developed. The important results here are that both of these techniques can be implemented as neural networks as front ends to subsequent neural network or conventional classifiers. This has significant long term implications since one of the great unsolved problems in science and engineering is how do animals interact with the environment. To do this the original noisy, analog, real-world data must be processed. The great hope for neural networks is that they can handle this problem. Our contribution to using neural networks (Gabor transforms) to find targets in real world images (segmentation) demonstrates that artificial neural networks can provide a means for processing real world data. Figure 3 below shows an original FLIR scene and the segmentation achieved by computing the Gabor transform of the image and adding together the resulting images for four orientations of the Gabor wavelets.

## 6 Optical Pattern Recognition

In the optical pattern recognition world we developed techniques which allow the processing of real FLIR images with existing binary spatial light modulators. A joint transform correlator was designed and tested using images of tactical targets. The binarization techniques were based on biological information on normalization in the Limulus eye. This is a demonstration of optical processing techniques that function with real world FLIR scenes with existing optical components. The techniques developed in this area allow us now to envision smart bombs with shape recognition being accomplished at photon speed instead of crunching large arrays of numbers in an embedded silicon computer in the front of a missile. The key to success for this correlator was the neuallly inspired binarization which allowed the display of the FLIR images on a binary spatial light modulator, a magneto-optic device.

## 7 Angle of Arrival Detection

Also in the area of optical processing, an optical direction of arrival detector, applicable to laser illumination direction determination, was designed and tested. The design is similar to a fly's eye. The intensity patterns from a fibre optic waveguide are processed to determine direction information. We proposed the fly's eye designed, built it, tested it and are now refining the neural network processing techniques in use. We obtained a one degree accuracy on the original prototype system.

## 8 Optical Operational Amplifier

Newly coated mirrors for the optical confocal Fabry Perot interferometer were designed, specified, fabricated and have now been delivered and installed on special mounts which we can electronically control. We spent the last six months characterizing the beam fanning phenomena. With this information and the newly fabricated mirrors we are now experimenting with the Optical Resonator as a testbed for a general purpose optical computer. Specifically we will test our design as an optical neural network (associative memory, as a clutter rejector, and an optical phase retrieval system). We have now demonstrated the optical computer stabilized and functioning and are in the process of inserting the nonlinear crystals which are necessary to do the applications listed above.

## 9 Speech Recognition and Processing

In the area of speech recognition we made significant progress in the use of neural networks for processing multiple feature sets for speech recognition. Although the accuracies are only comparable to other existing techniques the fact that the networks can be competitive here gives us hope that we now have alternatives.

Also in the area of speech processing, working with mutilated speech from Jim Cupples, RADC/IRRA, we have developed techniques to reconstruct speech using rules, rather than filters. We are now extending this work to see if it can be the basis of an effective speech recognizer and a low bit speech encoder.

## 10 Reverse VLSI Engineering

In the area of Reverse VLSI we developed techniques using the neural inspired Gabor Transform to find landmarks of interest such as the pads. As part of this effort we received and integrated a Sun 4, a digitizer, an optics bench and a laser microscope. This work is documented in a companion NAECON paper. This is a special case of the problem of using neural networks as front end processors for segmentation.

## 11 Multiplexed Brain Electrode

Lastly we are continuing work on a brain chip. The problem for the last couple of years is how to take commercially available chip fabrication technology, which uses aluminum, and replate these chips using platinum for implantation within a living monkey. We believe that this problem is now solved and hope for implantation this year.

## 12 Acknowledgements

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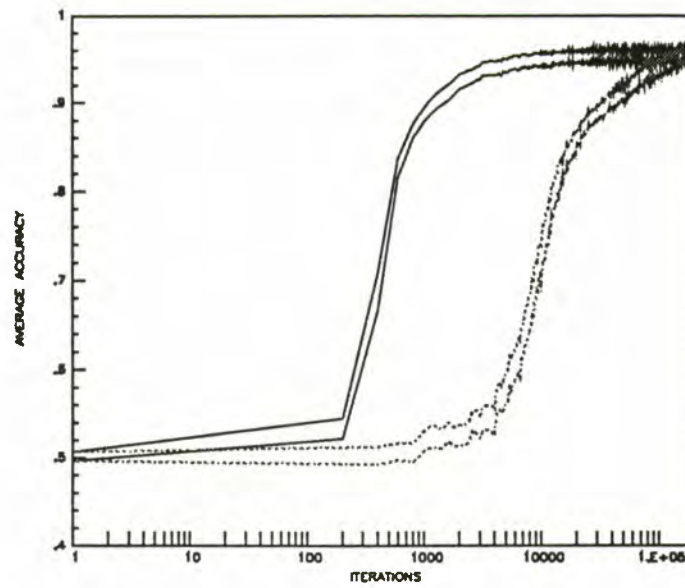


Figure 1: Average Training Accuracy for Exclusive-OR Problem - 90 confidence (solid: Kalman training; dotted: back propagation training);

Table 1: Overall FLIR Classification Accuracy (95% Confidence Interval)

Classifier	Accuracy Rate
Neural Network	(0.883,0.931)
Bayesian	(0.841,0.897)

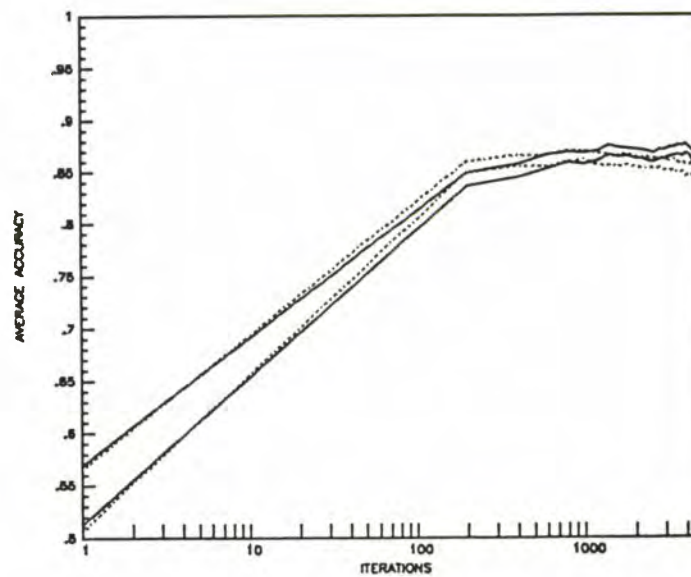


Figure 2: Average Testing Accuracy for Target/Non-target Problem on Absolute Range Data - 90% confidence (solid: back propagation; dotted: Kalman).





(a) Original FLIR Image



(b) Gabor Segmented FLIR Image

Figure 3: Artificial Neural Network Segmentation